Evaluating the potential of artificial neural network and neuro-fuzzy techniques for estimating antioxidant activity and anthocyanin content of sweet cherry during ripening by using image processing

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Abstract

BACKGROUND: This paper presents a versatile way for estimating antioxidant activity and anthocyanin content at different ripening stages of sweet cherry by combining image processing and two artificial intelligence (AI) techniques. In comparison with common time-consuming laboratory methods for determining these important attributes, this new way is economical and much faster. The accuracy of artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) models was studied to estimate the outputs. Sensitivity analysis and principal component analysis were used with ANN and ANFIS respectively to specify the most effective attributes on outputs.

RESULTS: Among the designed ANNs, two hidden layer networks with 11-14-9-1 and 11-6-20-1 architectures had the highest correlation coefficients and lowest error values for modeling antioxidant activity ($R = 0.93$) and anthocyanin content ($R = 0.98$) respectively. ANFIS models with triangular and two-term Gaussian membership functions gave the best results for antioxidant activity ($R = 0.87$) and anthocyanin content ($R = 0.90$) respectively.

CONCLUSION: Comparison of the models showed that ANN outperformed ANFIS for this case. By considering the advantages of the applied system and the accuracy obtained in somewhat similar studies, it can be concluded that both techniques presented here have good potential to be used as estimators of proposed attributes.

Keywords: antioxidant activity; anthocyanin content; cherry fruit; ANN; ANFIS; image processing

INTRODUCTION

Sweet cherry (Prunus avium) is a popular fruit consumed in both fresh and processed forms. With an annual production of around 241117 MT (metric ton), Iran is ranked as the third-highest sweet cherry-producing country in the world.1

Humans live in a highly oxidative environment, and many processes involved in metabolism may result in the production of excess free radicals, which can lead to health problems.2 Oxidation causes the formation of toxic compounds that are harmful to human health, such as reactive oxygen species and free radicals, which can lead to carcinogenesis, mutagenesis, inflammation, DNA changes, aging, cardiovascular disease and nutritional loss.3 – 5 In addition, oxidation may result in unpleasant flavor and rancid taste.6,7 There is growing interest among food producers and consumers in the use of natural antioxidants because of their protective role against oxidation.8 Thus it may be beneficial to find a rapid and non-destructive way for estimating this attribute in fruits as an important source of antioxidants.

Anthocyanins, which are among the most common plant pigments, appear to have multiple functions, for example as coloring agents and quality control markers of foodstuffs.9 Recently, increased understanding and awareness of their potentially beneficial effects on human health have led to intensified research on anthocyanins.10 Various data mining/artificial intelligence (DM/AI) techniques such as decision trees, artificial neural networks (ANNs), genetic algorithms, fuzzy sets, expert systems, etc. have been increasingly applied in combination with machine vision (MV) for agricultural product quality evaluation in recent years.11 – 14

A new field of image processing of agricultural products is being used to estimate some quality attributes such as plant
pigments and antioxidant activity. By applying independent component analysis to spectral images of tomatoes, Polder et al. estimated their lycopene and chlorophyll concentration. More recently, Taghadomi-Saberi et al. estimated the antioxidant activity and anthocyanin content of sour cherries during ripening by combining image processing and ANN techniques.

Given the facts that antioxidants have an important role in human life nowadays and that conventional methods for their determination are expensive, destructive and time-consuming, this study aims to propose, devise and evaluate the possibility of using an intelligent system based on a combination of MV and two widely used DM techniques for estimating the antioxidant activity and anthocyanin content of sweet cherries during ripening.

**EXPERIMENTAL**

The recommended framework for estimating antioxidant activity and anthocyanin content is shown in Fig. 1. First, images of sweet cherries were acquired and image-processing operations were applied to remove unwanted noise. Then some size and color features were extracted from segmented images. To achieve a good and rapid system, the extracted features were subjected to a selection technique to identify the effective ones. Then the relationship between the proposed attributes and the selected features of images was modeled by two widely used DM techniques, namely ANN and adaptive neuro-fuzzy inference system (ANFIS). Finally, the results of these techniques were compared. The complete modeling methodology is described in the following subsections.

**Sample preparation**

Cherry fruits obtained from a village garden were stored in a refrigerator after detachment of their stems. The senescence period of sweet cherry changes in six stages, from green to yellow, pink, light red, then to red and finally to black. Fruits at different ripening stages were chosen based on their color by visual inspection.

**Analytical methods**

A total of 420 sweet cherries were divided into 42 homochromatic groups of ten fruits each. The extracted juice from each group was centrifuged in a Mikro 220R centrifuge (Hettich Instruments, Tuttingen, Germany) at 3406 × g for 20 min at room temperature (−22 °C).

**Anthocyanin content**

The total anthocyanin content of sweet cherry juice was determined by a pH differential method using two buffer systems, potassium chloride buffer (pH 1) and sodium acetate buffer (pH 4.5), and the absorbance at 510 and 700 nm was read against a water blank at room temperature (−22 °C).

**Antioxidant activity**

The antioxidant activity of sweet cherry juice was determined by the 2,2-diphenyl-1-picrylhydrazyl (DPPH) method. The EC50 value was defined as the amount of sample necessary to decrease the initial DPPH concentration by 50% and expressed as mL sample g−1 DPPH according to the method of Cam et al. From each appropriately diluted sweet cherry juice sample, 0.1 mL was mixed with 3.9 mL of DPPH solution. The absorbance at 515 nm was measured at different time intervals using a Cecil CE 2502 UV–visible spectrophotometer (Cecil Instruments, Bath, UK) until the reaction reached the steady state condition.

**Image processing**

Three different color spaces, namely RGB, HSV and L’a’b’, were used in this study. The most common of these is the RGB model, in which each sensor captures the intensity of light in the red (R), green (G) or blue (B) spectrum respectively. The HSV color space, which is an ideal tool for developing image-processing algorithms based on some of the color-sensing properties of the human visual system, better represents how humans perceive color, owing to the varying levels of saturation and value. The L’a’b’ color space is device-independent and perceptually uniform; that is, the Euclidean distance between two different colors corresponds approximately to the color difference perceived by the human eye.

**Machine vision set-up**

To acquire the cherry images, an MV system was designed and implemented (Fig. 1). The proposed system consists of a color CCD camera (Model 565S, PROLINE UK, London, UK) equipped with a CS lens mount (3.5–8 mm focal length, 480 vertical TV lines resolution), a capture card (WinFast DV2000 with resolution 720H × 480V), a personal computer (PC) for image acquisition and display and an appropriate lighting system consisting of two fluorescent tube lamps. The camera was placed about 10 cm above the samples and powered by a 24 V power supply. After trial and error, a white background surface was chosen because of its good and acceptable contrast with cherries. In order to achieve uniform lighting and to eliminate environmental noise, the set-up frame was covered with tarpaulin during image acquisition. Captured signals from cherry samples were transferred to the PC through the video capture card, digitized and stored on the computer for further analysis.

**Cherry fruit segmentation**

Segmentation was carried out on the images to separate cherries from the background using HSV space. Then global thresholding was performed on different channels of the images using the Otsu method. Otsu is a histogram-based thresholding method in which
the normalized histogram is considered as a discrete probability density function. The saturation parameter (S) was effective to segment the cherry from the background. It was found that simple thresholding on just one channel was not efficient because of the varying color of cherries at different ripening stages, possible juice spots and possible noise due to shadows or reflections. Accordingly, the ‘if’ command for using different channels and the morphological operators in the image-processing toolbox of MATLAB software (MathWorks, Natick, MA, USA) were applied.

Characterization of fruit images
From the segmented images of sweet cherries, a set of features was extracted to describe each sample. The feature analyses of cherry included the extraction of color features in RGB and L*a*b* (CIE) spaces and just one size feature indicating the pixel number of segmented cherry. Altogether, 34 features, including some statistical parameters of color matrices (R, G and B) or their differences and ratios and some CIE parameters such as C*, hue and browning index (BI), were extracted for each cherry. Some of the computed features are listed below (Eqns (1)–(15)):

\[
\begin{align*}
t_1 & = \frac{R}{(R+G+B)} \\
 r_{,m} & = \text{mean} \ (R) \\
 r_{,g} & = R - G \\
 v_{,r} & = \text{var} \ (R) \\
 \text{skew}_r & = \text{skewness} \ (R) \\
 \text{kor}_r & = \text{kurtosis} \ (R) \\
 m_{,r,g} & = \text{mean} \ (r_{,g}) \\
 v_{,r,g} & = \text{var} \ (r_{,g}) \\
 \text{skew}_r & = \text{skewness} \ (r_{,g}) \\
 \text{kor}_r & = \text{kurtosis} \ (r_{,g}) \\
 \text{skew}_t_1 & = \text{skewness} \ (t_1) \\
 \text{kor}_t_1 & = \text{kurtosis} \ (t_1) \\
 \text{hue} \ (H^*) & = \tan^{-1} \left( \frac{b^*}{a^*} \right) \\
 \text{chroma} \ (C^*) & = \left( a^* + b^* \right)^{1/2} \\
 \text{BI} & = \left[ \left( 100 (x - 0.031) \right) / 0.17 \right]
\end{align*}
\]

where \(x = (a^* + 1.75L^*) / (5.645L^* + a^* - 3.012b^*)\) and var is the ‘variance’ command in MATLAB software. Note that, when \(a^* < 0\) and \(b^* > 0\), hue angle \(H^* = 180^\circ + \tan^{-1}(b^*/a^*)\).

Feature selection
In DM applications, selection of a suitable feature vector is essential. Selection of the best features is one of the key factors in improving performance; features that do not improve classification accuracy should be discarded from the feature vector. Three commonly used techniques applicable for this purpose are principal component analysis (PCA), correlation-based feature selection and sensitivity analysis. An effective procedure to reduce the dimension of the input vector is using sensitivity analysis in NeuroSolutions 5.0 software (NeuroDimension Inc., Gainesville, FL, USA) to specify the most effective attributes on outputs.

After applying sensitivity analysis, the size of the feature vector was reduced from 34 features to the 11 features presented in Table 1; that is, by using sensitivity analysis, a 67.65% reduction in features was achieved.

Intelligent techniques for modeling proposed properties
In the present paper, two widely used AI techniques, namely ANN and ANFIS, were used for modeling the relationship between extracted features and antioxidant activity and anthocyanin content of sweet cherry during ripening. To find the best technique for modeling the two proposed quality attributes, these techniques were evaluated using MATLAB software.

Artificial neural networks (ANNs)
ANNs are machine-learning models that simulate the behavior of the human brain. They are composed of a large number of highly interconnected processing elements that are analogous in functionality to biological neurons and are tied together with weighted connections corresponding to brain synapses. The multilayer perceptron (MLP) is a common and widely used type of ANN. MLPs focus on building intelligent codes by constituting a parallel connected network model. In an MLP model called the ‘universal function approximator’, once the system is trained, the network can calculate outputs as a functional mapper using the last updated network parameters. MLPs belong to the class of feedforward networks, meaning that information passes among the network nodes exclusively in the forward direction. Here we used a Levenberg–Marquardt algorithm for error minimization, and training of the MLP model was performed using a back-propagation algorithm. ANN generation routines integrated into software programmed in MATLAB convert the extracted features of the sweet cherry images over the whole fruit pixels shown in the images into desired outputs. A total of 400 ANN architectures were designed and tested with two hidden layers and a variable number of neurons from one to 20 in each layer in every run.

Adaptive neuro-fuzzy inference system (ANFIS)
The ANFIS model is a combination of a neural network and a fuzzy inference system in such a way that the neural network is used to determine the parameters of the fuzzy inference system. It combines the advantages of fuzzy systems, which deal with explicit knowledge that can be explained and understood, and neural networks, which deal with implicit knowledge that can be acquired by learning. The fuzzy logic also enhances the generalization capability of a neural network by providing more reliable output when extrapolation is needed beyond the limits of the training data. This form of neuro-fuzzy approach provides a means of training a family of membership functions to emulate a nonlinear, multidimensional mapping function. The ANFIS approach integrates the basic elements and functions of a conventional fuzzy inference system into the neural network connective structure, which distributes the learning ability to obtain the membership functions and fuzzy logic rules. The ANFIS consists of five layers of nodes: a fuzzification layer, a rule layer, a normalization layer and a defuzzification layer that produce the overall output layer.

In the present study a hybrid algorithm combining the least squares method and the gradient descent method was adopted.
to solve the adaptive modifiable parameters in the first (premise parameters) and fourth (consequent parameters) layers. The gradient descent method was used to optimally adjust the premise parameters corresponding to membership functions of the input domain, and the least squares method was used to optimize the consequent parameters.

In order to use the ANFIS technique, decreasing dimension is necessary. By using PCA in MATLAB software, four principal components (PCs) were selected from the resulting data from the ‘Feature selection’ subsection, i.e. 11 attributes abstracted into four elements. These features were then fed to ANFIS models as input vector.

### Statistical analysis
To evaluate model performance, three criteria, namely root mean square error (RMSE), mean absolute error (MAE) and correlation coefficient ($R$), were used. These statistical criteria can be expressed mathematically as follows:

$$\text{RMSE} = \left( \frac{1}{n} \sum_{i=1}^{n} (P_i - O_i)^2 \right)^{1/2} \quad (16)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |P_i - O_i| \quad (17)$$

where $P_i$ is the predicted value, $O_i$ is the observed value and $n$ is the number of observations.

### RESULTS

#### Modeling by ANNs
To have a significant influence on the learning rate and final accuracy of a network, the network architecture is an important factor in designing ANNs. The factors that can be changed in this case are the number of hidden layers and their number of neurons. The numbers of neurons in the input (11 extracted features) and output (antioxidant or anthocyanin) layers were fixed. Several networks with two hidden layers were designed, trained and generalized with the back-propagation algorithm and a varying number of neurons from one to 20 in each hidden layer. Based on selection criteria ($R$, RMSE and MAE), best architectures were chosen. The results obtained from five models and their characteristics are illustrated in Table 2 for both antioxidant activity and anthocyanin content.

### Antioxidant activity
A network with 11-14-9-1 architecture achieved the best performance, without overtraining, i.e. the best model consisted of an input layer with 11 input variables, two hidden layers with 14 and nine neurons respectively and an output layer with one output variable (antioxidant activity), highlighted in bold type in Table 2. This neural network used $\text{trainlm}$ as training function and $\text{tansig}$ as transfer function. This architecture showed the best values of performance criteria ($R = 0.93$, RMSE = 0.34 and MAE = 0.27) for modeling the antioxidant activity of sweet cherry during ripening (Fig. 2a).

### Anthocyanin content
As can be seen in Table 2, the 11-6-20-1 network was selected as the best topology for modeling the anthocyanin content of sweet cherry during ripening. This back-propagation neural network using $\text{trainlm}$ as training function and $\text{tansig}$ as transfer function had the highest correlation coefficient (0.98) (Fig. 2b) and the lowest values of MAE (0.13) and RMSE (0.67).

#### Modeling by ANFIS
The number and type of membership function (MF) for each input are two main factors among many parameters that can be tuned to obtain better results in ANFIS. Accordingly, five different MF types ($\text{trimf}$, $\text{gbellmf}$, $\text{gaussmf}$, $\text{gauss2mf}$ and $\text{pimf}$) and three MF numbers were used to investigate different structures and obtain the best one. Test data were used to detect overtraining of the training data set. The ANFIS model was set up for modeling the antioxidant activity and anthocyanin content of sweet cherry during ripening by using the parameters listed below.

- Initial FIS generation method = ‘grid partition’
- Number of MFs = 2, 3 and 4
- Input MFs type = ‘trimf’, ‘gbellmf’, ‘gaussmf’, ‘gauss2mf’ and ‘pimf’
- Output MF type = ‘linear’
- Step size = adaptive (initial = 0.04, decrease rate = 0.9, increase rate = 1.1)

### Table 1. Selected features using sensitivity analysis for modeling antioxidant activity and anthocyanin content

<table>
<thead>
<tr>
<th>Modeling</th>
<th>Selected features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Antioxidant</td>
<td>Pixel no.</td>
</tr>
<tr>
<td></td>
<td>$b_\text{mean}$</td>
</tr>
<tr>
<td>Anthocyanin</td>
<td>Pixel no.</td>
</tr>
<tr>
<td></td>
<td>$\text{kor}_t_3$</td>
</tr>
</tbody>
</table>

$t_3 = b/(r + g + b)$. 

$t_3$ is the predicted value, $O_i$ is the observed value and $n$ is the number of observations.
Table 2. Performance of neural network results

<table>
<thead>
<tr>
<th>ANN output</th>
<th>$N_{h1}$</th>
<th>$N_{h2}$</th>
<th>RMSE</th>
<th>MAE</th>
<th>$R$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Antioxidant activity</td>
<td>9</td>
<td>14</td>
<td>0.5644</td>
<td>0.3603</td>
<td>0.7986</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>15</td>
<td>0.5320</td>
<td>0.3544</td>
<td>0.8222</td>
</tr>
<tr>
<td></td>
<td>14</td>
<td>9</td>
<td>0.3353</td>
<td>0.2666</td>
<td>0.9347</td>
</tr>
<tr>
<td></td>
<td>17</td>
<td>17</td>
<td>0.4454</td>
<td>0.3112</td>
<td>0.8786</td>
</tr>
<tr>
<td></td>
<td>19</td>
<td>9</td>
<td>0.5098</td>
<td>0.3275</td>
<td>0.8439</td>
</tr>
<tr>
<td>Anthocyanin content</td>
<td>6</td>
<td>20</td>
<td>0.6689</td>
<td>0.1266</td>
<td>0.9756</td>
</tr>
<tr>
<td></td>
<td>14</td>
<td>20</td>
<td>0.3962</td>
<td>0.1994</td>
<td>0.9210</td>
</tr>
<tr>
<td></td>
<td>15</td>
<td>18</td>
<td>0.4158</td>
<td>0.1992</td>
<td>0.9080</td>
</tr>
<tr>
<td></td>
<td>17</td>
<td>4</td>
<td>1.2888</td>
<td>0.4900</td>
<td>0.5579</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>12</td>
<td>0.9611</td>
<td>0.1801</td>
<td>0.7004</td>
</tr>
</tbody>
</table>

$N_{h1}$, number of neurons in $i$th hidden layer; RMSE, root mean square error; MAE, mean absolute error; $R$, correlation coefficient.

Figure 2. Correlation between laboratory results and predicted values of (a) antioxidant activity and (b) anthocyanin content using ANN.

- Epoch number: 100
- Learning algorithm: hybrid

**Antioxidant activity**

The results of modeling the proposed attributes by ANFIS are shown in Table 3. The best result for modeling antioxidant activity was obtained with two triangular MFs. For this model the values of $R$, RMSE and MAE were 0.87 (Fig. 3a), 0.49 and 0.34 respectively. When the number of input MFs was increased from two to four, the ANFIS model produced redundancy in the data structure, hence the error values increased and the correlation coefficient decreased.

**Anthocyanin content**

According to the results of modeling anthocyanin content shown in Table 3, increasing the number of MFs also led to a decrease in $R$ and an increase in the error values. The two-term Gaussian MF was chosen as the best ANFIS model for modeling anthocyanin content. This structure had the highest correlation coefficient (0.90) (Fig. 3b) and the lowest value of RMSE (0.44).

**DISCUSSION**

Antioxidant activity decreased during the earlier stages of development and then increased progressively until the end of the ripening process (Fig. 4a). This increase to maximum activity at stage 6 showed anthocyanin accumulation and fruit darkening. Such behavior is similar to that found in previous research on sweet cherry. An absolute increase was observed in anthocyanin content, with very low concentrations between stages 1 and 3 and a sharp increase from stage 4 until stage 6, when the highest anthocyanin concentration was reached (Fig. 4b). Serrano et al. and Polder et al. reported similar changes in the evolution of plant pigments over the developmental stages of sweet cherry and tomato fruits respectively. The beginning of the anthocyanin increase coincided with a decrease in the color parameter $a^*$ (Fig. 4c). This means that the anthocyanin content remained constant with increasing $a^*$ value until stage 3, after which the $a^*$ value of sweet cherry decreased while the anthocyanin content increased until the end of the ripening process.

Polder et al. determined the lycopene concentration ($Q^2 = 0.95$) in tomato fruits using imaging spectrometry and a supervised method. In comparison with other studies, the correlation coefficients obtained in the present study show that our system can be...
Table 3. Performance of ANFIS results

<table>
<thead>
<tr>
<th>Output</th>
<th>Number of input MFs</th>
<th>Criterion</th>
<th>trimf</th>
<th>gbellmf</th>
<th>gaussmf</th>
<th>gauss2mf</th>
<th>pimf</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Antioxidant activity</strong></td>
<td>2</td>
<td>R</td>
<td>0.8723</td>
<td>0.8145</td>
<td>0.8437</td>
<td>0.7249</td>
<td>0.6289</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td></td>
<td>0.4929</td>
<td>0.6505</td>
<td>0.5713</td>
<td>0.8838</td>
<td>1.1180</td>
</tr>
<tr>
<td></td>
<td>MAE</td>
<td></td>
<td>0.3416</td>
<td>0.3563</td>
<td>0.3293</td>
<td>0.3420</td>
<td>0.3948</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>R</td>
<td>0.4343</td>
<td>0.4813</td>
<td>0.6600</td>
<td>0.4839</td>
<td>0.5726</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td></td>
<td>1.5067</td>
<td>1.3443</td>
<td>0.8649</td>
<td>1.0965</td>
<td>1.0010</td>
</tr>
<tr>
<td></td>
<td>MAE</td>
<td></td>
<td>0.5785</td>
<td>0.5509</td>
<td>0.4940</td>
<td>0.5868</td>
<td>0.5534</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>R</td>
<td>0.3129</td>
<td>0.4368</td>
<td>0.3942</td>
<td>0.2286</td>
<td>0.3667</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td></td>
<td>2.0856</td>
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<td>1.6877</td>
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<td>1.9141</td>
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<tr>
<td></td>
<td>MAE</td>
<td></td>
<td>0.7271</td>
<td>0.5903</td>
<td>0.5844</td>
<td>0.6897</td>
<td>0.6675</td>
</tr>
<tr>
<td><strong>Anthocyanin content</strong></td>
<td>2</td>
<td>R</td>
<td>0.8010</td>
<td>0.8939</td>
<td>0.8844</td>
<td>0.8966</td>
<td>0.8948</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td></td>
<td>0.5990</td>
<td>0.4484</td>
<td>0.4666</td>
<td>0.4423</td>
<td>0.4459</td>
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<tr>
<td></td>
<td>MAE</td>
<td></td>
<td>0.3969</td>
<td>0.2611</td>
<td>0.2584</td>
<td>0.2502</td>
<td>0.2558</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>R</td>
<td>0.6783</td>
<td>0.7571</td>
<td>0.5698</td>
<td>0.8239</td>
<td>0.7499</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td></td>
<td>0.9341</td>
<td>0.8135</td>
<td>1.0892</td>
<td>0.6633</td>
<td>0.8026</td>
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<tr>
<td></td>
<td>MAE</td>
<td></td>
<td>0.3032</td>
<td>0.2840</td>
<td>0.3559</td>
<td>0.2504</td>
<td>0.2431</td>
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<tr>
<td></td>
<td>4</td>
<td>R</td>
<td>0.5931</td>
<td>0.4491</td>
<td>0.4219</td>
<td>0.7025</td>
<td>0.4262</td>
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<tr>
<td></td>
<td>RMSE</td>
<td></td>
<td>1.1238</td>
<td>1.7466</td>
<td>1.9005</td>
<td>0.9059</td>
<td>1.7798</td>
</tr>
<tr>
<td></td>
<td>MAE</td>
<td></td>
<td>0.3760</td>
<td>0.3216</td>
<td>0.4341</td>
<td>0.2248</td>
<td>0.3998</td>
</tr>
</tbody>
</table>

Figure 3. Correlation between laboratory results and predicted values of (a) antioxidant activity and (b) anthocyanin content using ANFIS.

Figure 4. Changes in (a) antioxidant activity, (b) anthocyanin content and (c) color values during ripening.
used for determining the antioxidant activity, anthocyanin content and other relevant attributes such as pH changes of sweet cherry during the ripening process with a very-low-cost CCD camera and without destructive, expensive and time-consuming tests.

Comparison of the models showed that the ANN models performed better than the ANFIS models in estimating the antioxidant activity and anthocyanin content of sweet cherry during ripening. The values of $R$ and MAE for antioxidant activity were 0.93 and 0.27 with ANN and 0.87 and 0.34 with ANFIS respectively, while those for anthocyanin content were 0.98 and 0.13 with ANN and 0.90 and 0.25 with ANFIS respectively.

Various DM/Al techniques have been successfully applied for agricultural product quality evaluation in recent years. Depending on the particular case study, each of these techniques can be useful. For instance, using genetic algorithm\textsuperscript{11} or ANN\textsuperscript{12} models for raisin sorting, ANN models for quality evaluation of Mazafati date fruit\textsuperscript{13} and ANN models for quality evaluation of chickpeas\textsuperscript{14} resulted in overall accuracies of 96.33, 98.13 and 93.00\% respectively. Mollazade \textit{et al.}\textsuperscript{12} used four different DM techniques, among which a 7-6-4 ANN had the highest correlation coefficient for grading raisins. There are also many other reports of the successful employment of different DM techniques, especially ANNs, in the food industry.

\section*{CONCLUSION}

This paper has presented a low-cost, non-destructive and rapid way to estimate the antioxidant activity and anthocyanin content of sweet cherry during ripening. Back-propagation ANNs with \textit{trainlm} as training function and \textit{tansig} as transfer function were used. Networks with 11-14-9-1 and 11-6-20-1 architectures gave the best results ($R = 0.93$ and 0.98) for modeling antioxidant activity and anthocyanin content respectively. A neuro-fuzzy technique was also applied for modeling the proposed attributes. Among others, triangular and two-term Gaussian MFs gave the best results ($R = 0.87$ and 0.90) for antioxidant activity and anthocyanin content respectively. Based on statistical criteria, ANN models achieved better results in modeling sweet cherry attributes. However, by considering the advantages of the applied system in comparison with normal laboratory methods for determining proposed attributes and the accuracy obtained by other researchers in somewhat similar studies, it can be concluded that both techniques presented here have good potential to be used as estimators of proposed attributes.

In the light of the present results, some suggestions can be considered and explored in future research.

\begin{itemize}
\item Use other AI techniques and evaluate their performances to choose the best one.
\item Use spectral images, which certainly have better accuracy.
\item Develop the algorithms proposed here for fruits of other colors.
\end{itemize}

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\section*{REFERENCES}


